TerraSwarm

A Machine Learning and Optimization Toolkit for the Swarm

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Overview

1. Motivation
2. Overview of Current ML Toolkit Capabilities
3. Case Study: Cooperative Robot Localization and Control
   - State Estimation: Particle Filtering
   - Path Planning: Information Based Methods for Robot Trajectory Optimization
   - Actor-oriented Design for State Space Dynamics and Measurements

4. Future Directions &Conclusions

Motivation

ML technology in programming languages:

- MATLAB, Python, Octave, Julia, R ...

And in the form of toolkits:

- **GMTK**, **StreamLab**, SHOGUN, Weka,...

The state-of-the-art tools traditionally interact with data and present no native way of incorporating system aspects

Goal: to make the ML aspects a native part of the system design by

- Exploiting component-level interactions in the swarm
- Restoring the **system level roots of machine learning methodologies** by providing the **right interfaces** between machine learning tools and CPS design aspects.

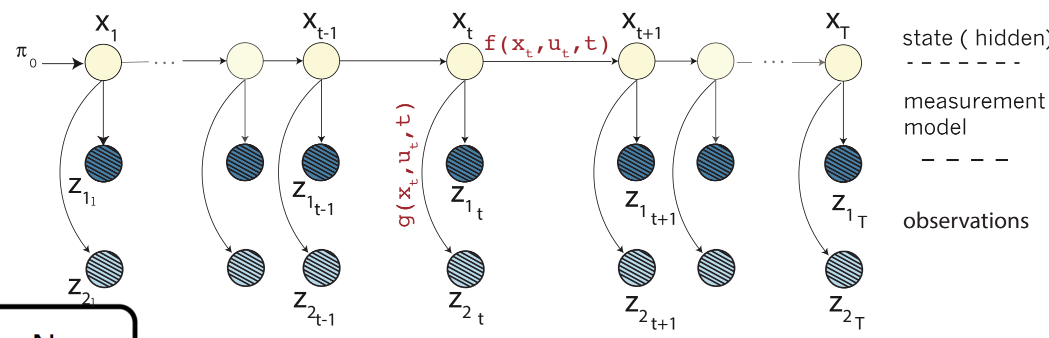
Motivation

We present an actor-oriented machine learning toolkit that focuses on

- Applications of ML Algorithms to **streaming data**
- Enabling ML techniques to be natively integrated into system design
- Context-aware parameterization of a rich set of ML algorithms
- Library of **easy-to-use tools** for developers who are not ML experts
- Enhancing **programmability** of *swarmlets*

Inference for Streaming Data

Goal : Inference on data that is evolving in *time*



Bayesian Networks

General Bayesian Nets

Arbitrary Graphical Model

Dynamic Bayesian Nets

Hidden Markov Model

$$x_0 \sim \mu_0$$
$$p(x_{t+1}|x_t) = A_{x_t, x_{t+1}}$$
$$y_t|x_t \sim g(x_t, \theta_t)$$

State Space Model

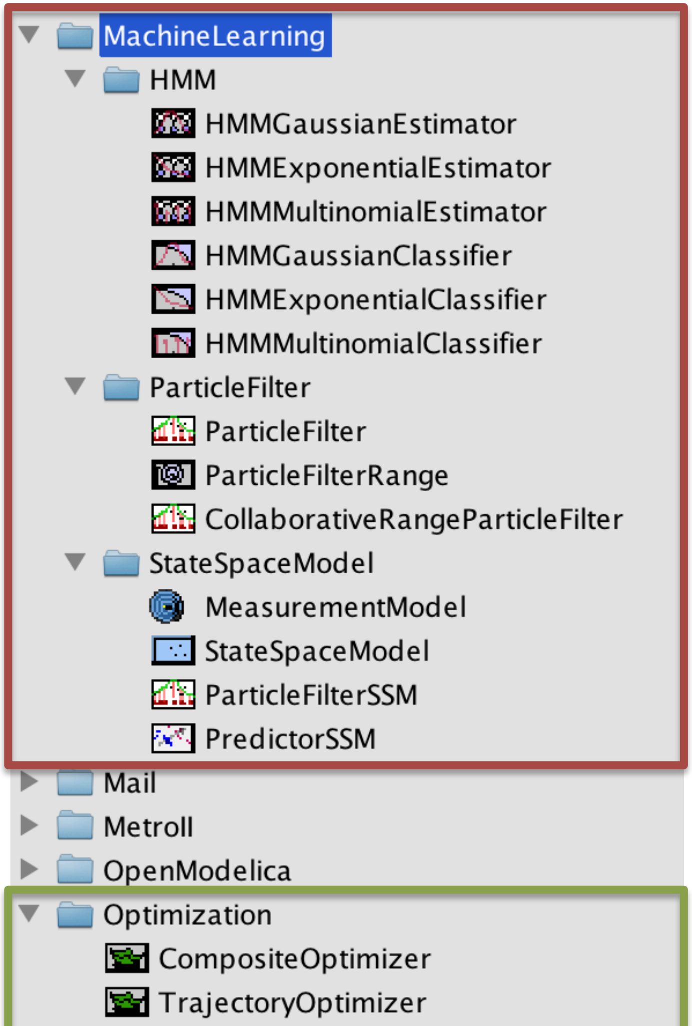
$$x_0 \sim \mu_0$$
$$x_{t+1}|x_t \sim f(x_t, u_t, t)$$
$$y_t|x_t \sim g(x_t, \theta_t)$$

Linear/Gaussian

Kalman Filter

$$x_0 \sim N(0, \mathbf{P}_t)$$
$$\mathbf{x}_t = \mathbf{F}_t \mathbf{x}_{t-1} + \mathbf{B}_t \mathbf{u}_t + \mathbf{w}_t$$
$$\mathbf{y}_t = \mathbf{H}_t \mathbf{x}_t + \mathbf{v}_t$$
$$\mathbf{w}_t \sim N(0, \mathbf{Q}_t), \mathbf{v}_t \sim N(0, \mathbf{R}_t)$$

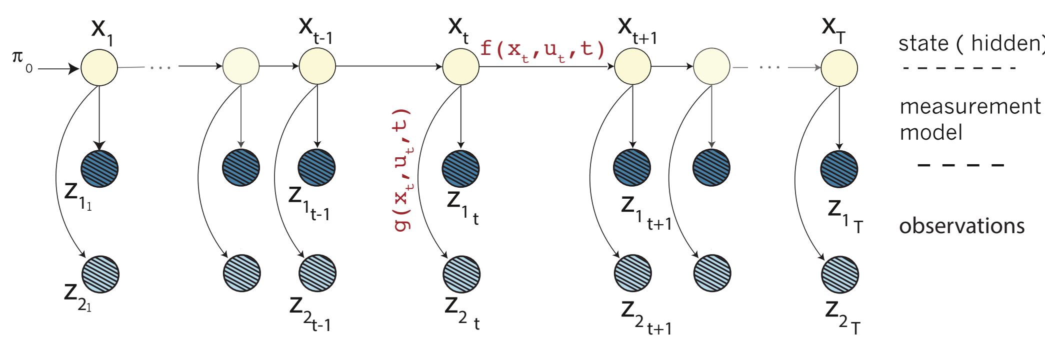
The Machine Learning Toolkit in Ptolemy II



Machine Learning:

1. Hidden Markov Models (HMM)
2. Gaussian Mixture Models (GMM)

- Parameter Estimation
- Classification



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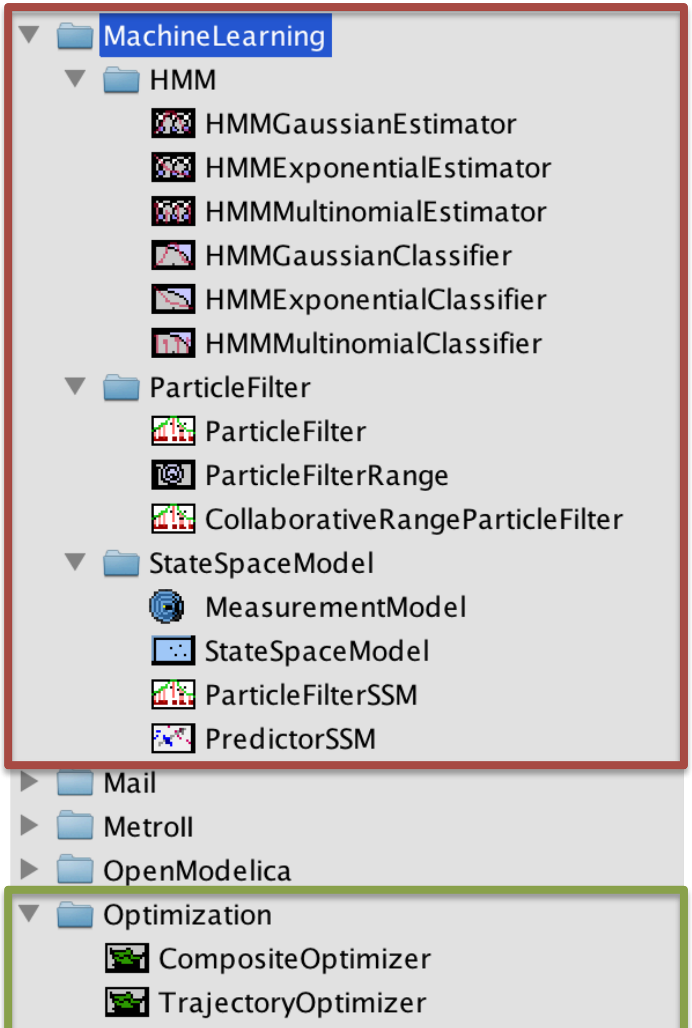
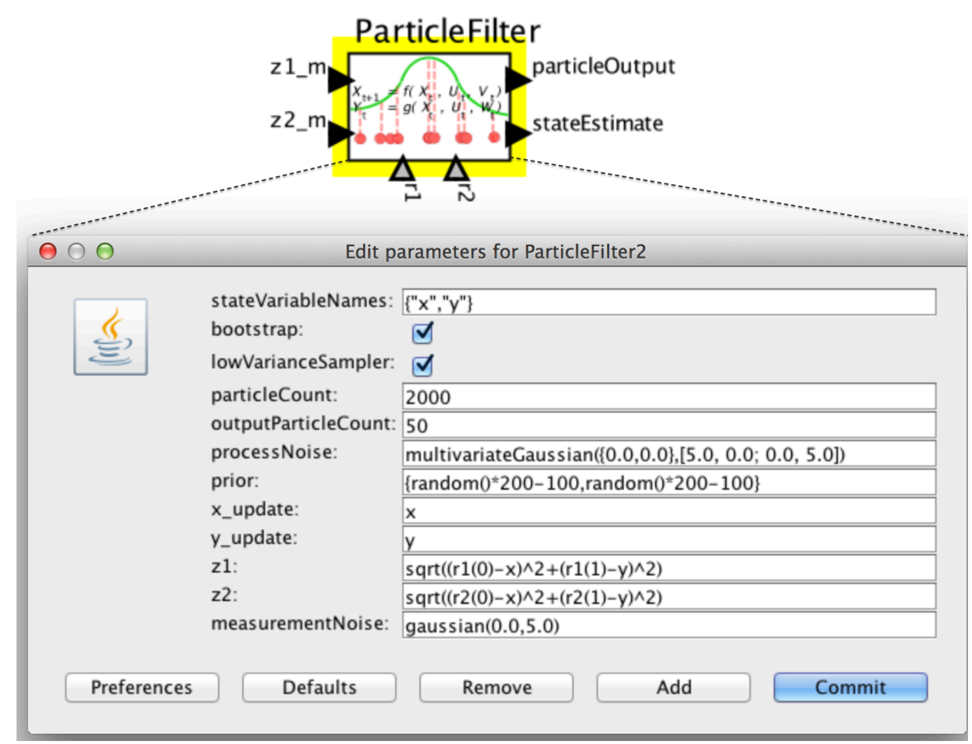


State Estimation:

- Particle Filtering



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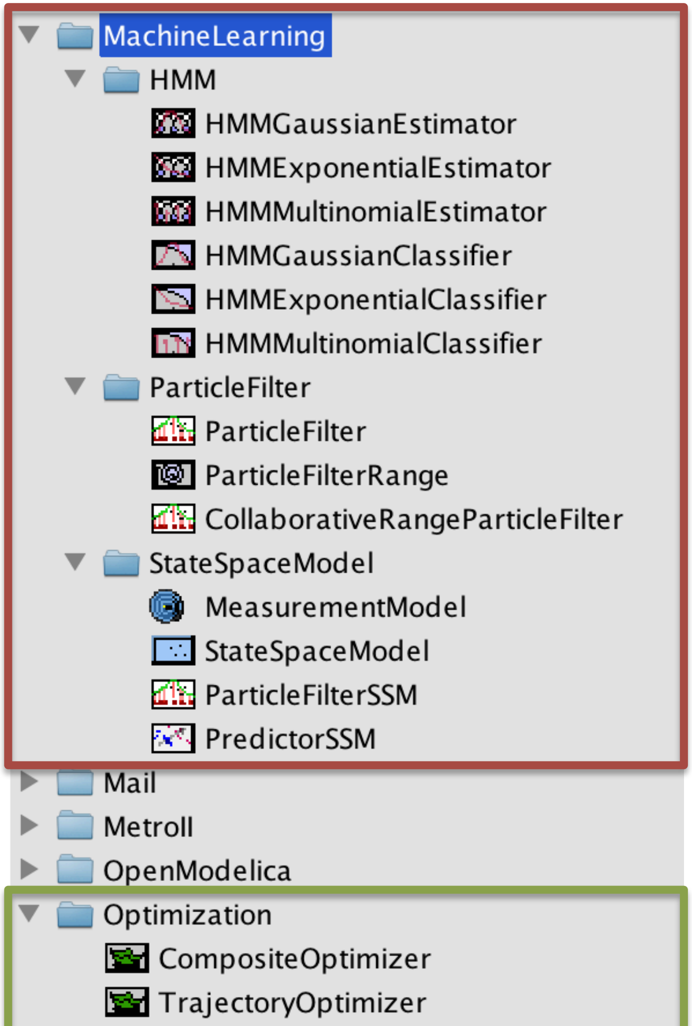
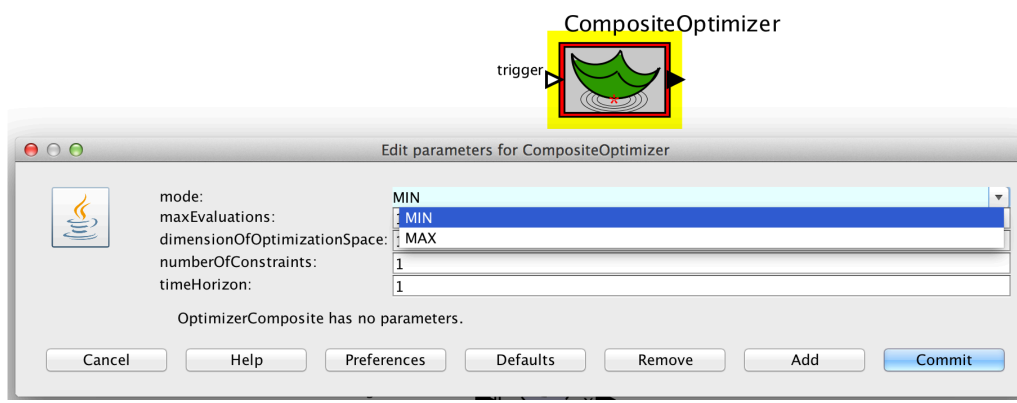


Optimization:

- CompositeOptimizer: An actor-oriented gradient-descent solver



Application: Swarmlets for Cooperative Robot Control

Problem Definition: A team of robots, tracking/pursuing a target.

Model: State Space Model of target dynamics

Observations: Robot sensor measurements (generally nonlinear functions of target position + noise)

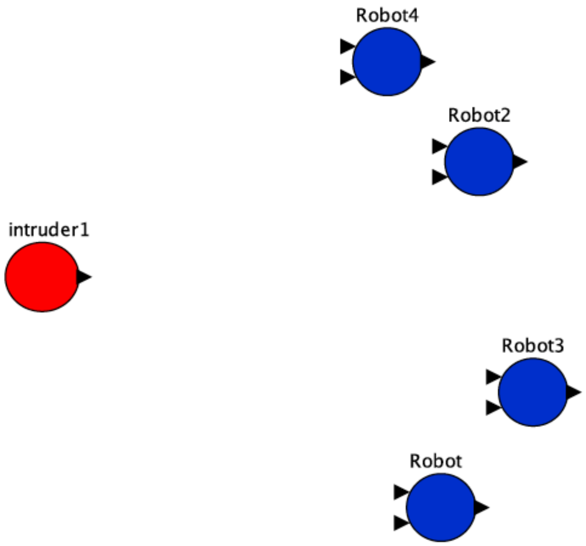
Tasks:

- *Target State Estimation*
- *Robot Path Planning: Multiple Objectives*

  Collision/Obstacle Avoidance, Pursuit, SLAM, Fast Localization, Minimal Uncertainty, …

Cooperative Robot Control : Challenges

- *Cooperation between robots*
- *Complex measurement/noise models*
    - *Range Measurements (e.g., RSSI)*
    - *Bearings Measurement (e.g., Cameras)*
- *Nonlinear robot dynamics*
- *Unknown Environment*



Cooperative Robot Localization: State Space Models

$$\theta_t = \begin{bmatrix} x_t \\ y_t \end{bmatrix}$$ Target state (position)

$$x_0 \sim \texttt{Uniform}([-100, 100])$$

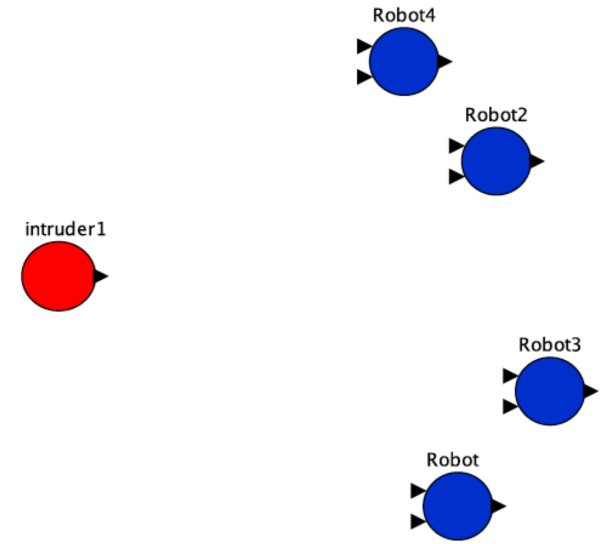
$$y_0 \sim \texttt{Uniform}([-100, 100])$$

$$\mathbf{z}_t = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$ Range Measurements

$$z_{it} = \|r_{it} - \theta_t\| + \omega_t, \ i = 1, 2$$ Measurement model

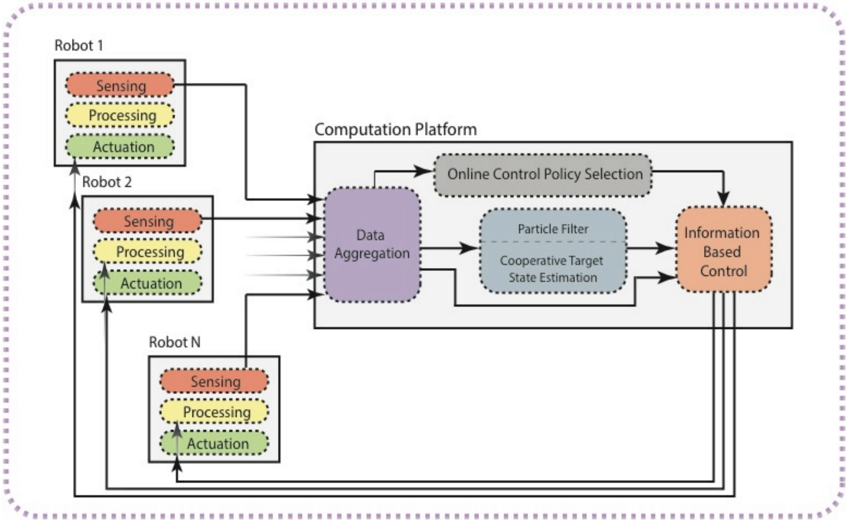
$$\omega_t \sim \mathcal{N}(0, \sigma^2), \sigma^2 = 5.0$$

$$\theta_{t+1} = \theta_t + \nu_t, \ \nu_t \sim \mathcal{N}(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 5.0 & 0.0 \\ 0.0 & 5.0 \end{bmatrix})$$ Target state dynamics



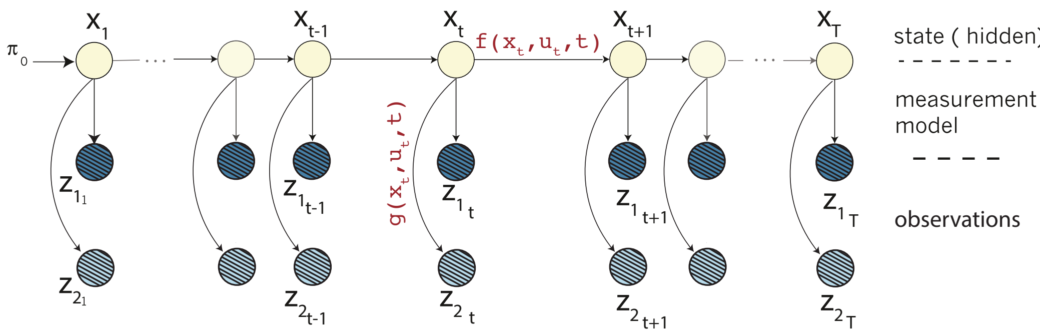
Algorithm Workflow

1. Robots make independent range measurements
2. A centralized (or local) cooperative state estimation algorithm estimates target position given measurements
3. Robot trajectories are optimized w.r.t. some objective function based on the estimated target position
4. Robots move according to the planned path



Target State Estimation

$$x_0 \sim \pi_X(x_0)$$
$$\mathbf{z_t}|x_t \sim g(x_t, u_t, t)$$
$$x_{t+1}|x_t \sim f(x_t, u_t, t)$$



- Given z_t, t=1,...T: noisy measurements of a target state x_t,
- Estimate $p(x_T \mid z_{1:T})$: Posterior density of the target state

$$\hat{p}(x_t) = p(x_t|\mathbf{z}_{1:t}) = \sum_{i=1}^{N} w_t^i \delta(x_t - \tilde{x}_t^i)$$

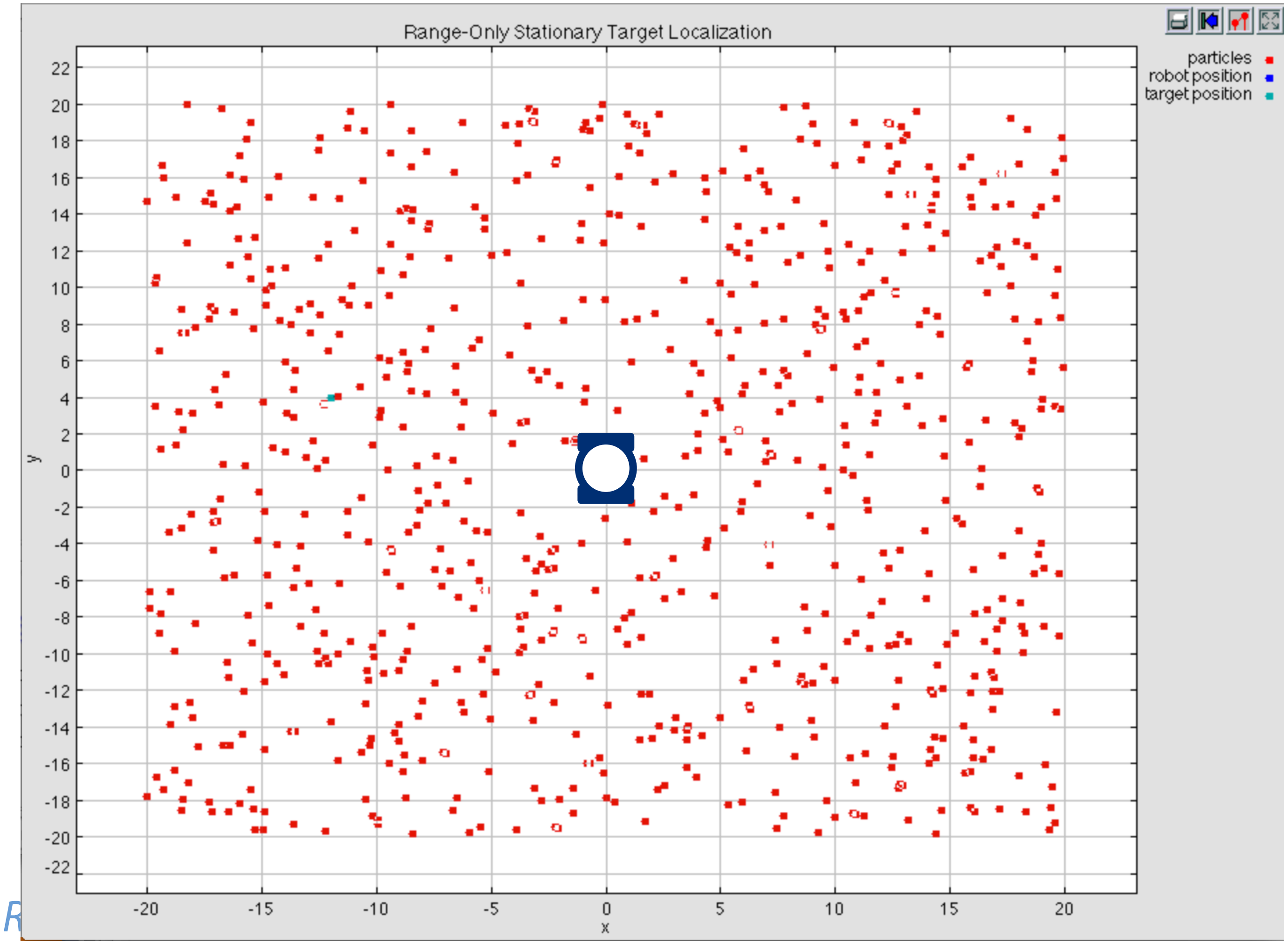
- Particle filtering is a popular Bayesian Filtering technique to solve this problem: Provides a density estimate of x_T as a particle set

The Particle Filter

- Introducing the particle filter:
  - Sequential Monte Carlo methods as a general family
  - A Bayesian filter that performs maximum-likelihood state estimation for state-space models with
    - nonlinear dynamics and non-Gaussian noise, in the general case
    - A stochastic (and often better performing) alternative of the Kalman filter (which is only optimal for the linear Gaussian case)

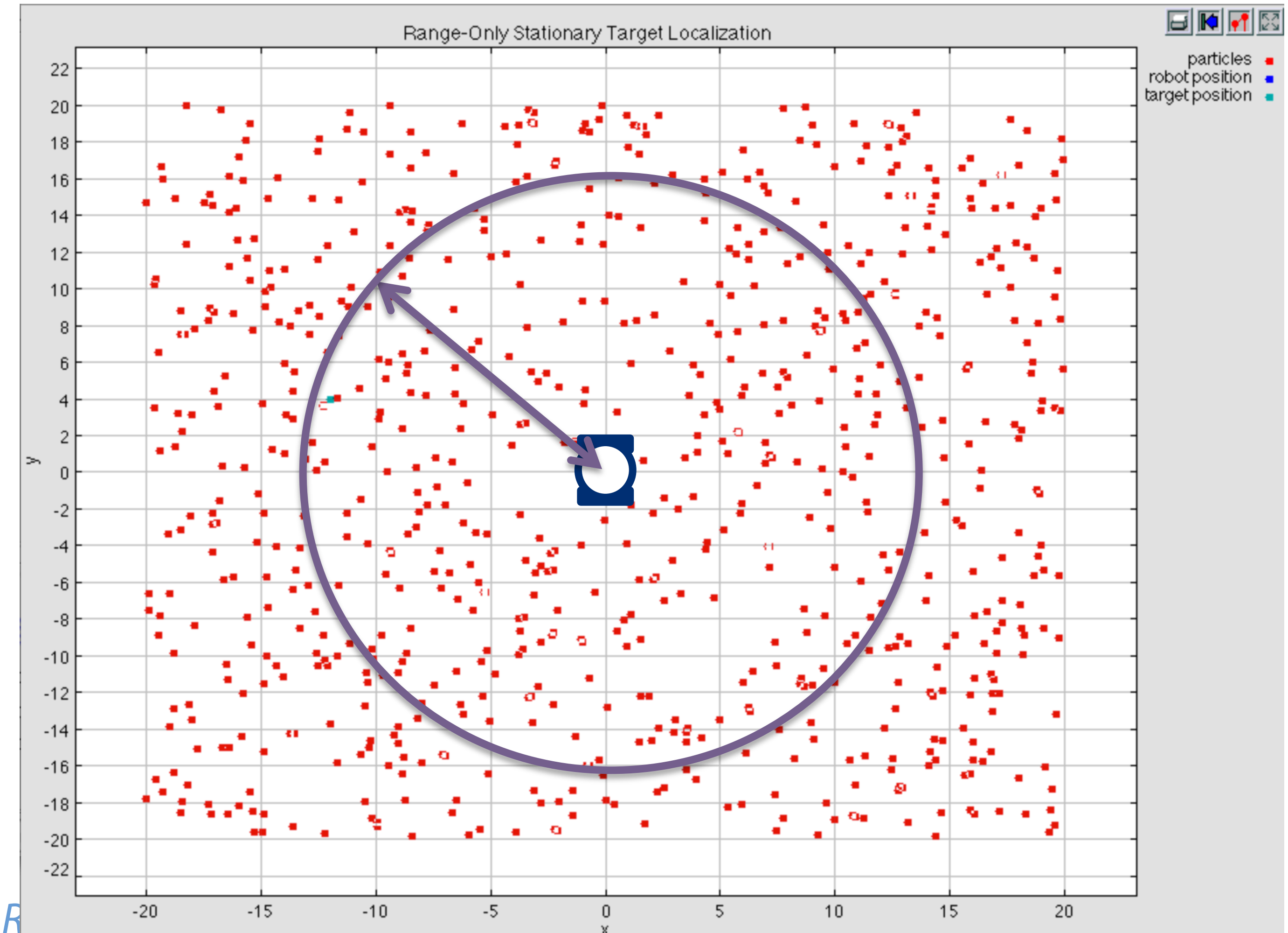
Particle Filter: Operation

- Establish a prior belief of the state, represented as a set of particles
- Each particle is a candidate "state", which is the intruder position in this particular application



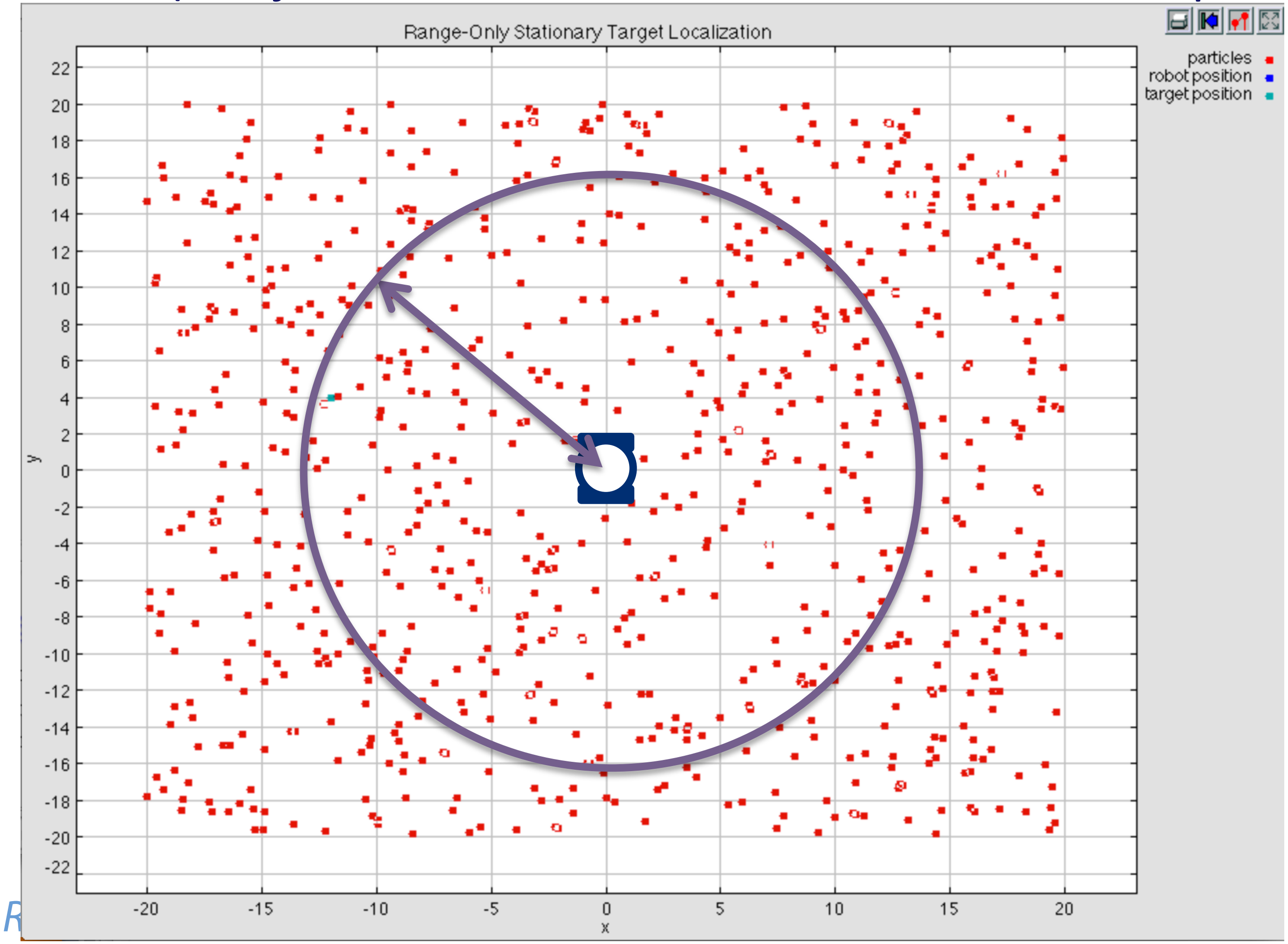
Particle Filter: Operation

- Make a measurement



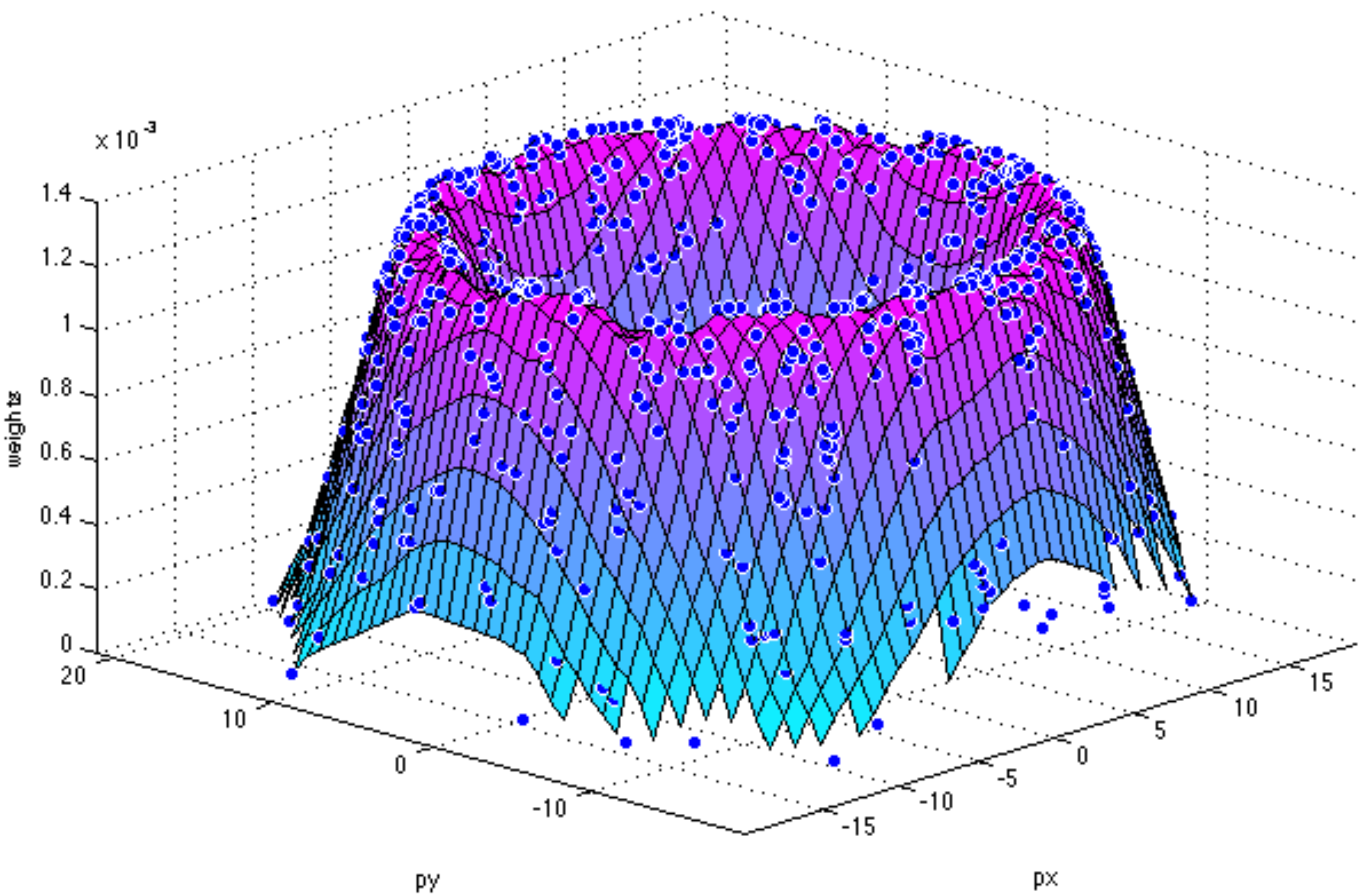
Particle Filter: Assigning Weights

- Assign weights to each particle according to how well it explains the measurement (subject to a measurement model and noise specification)



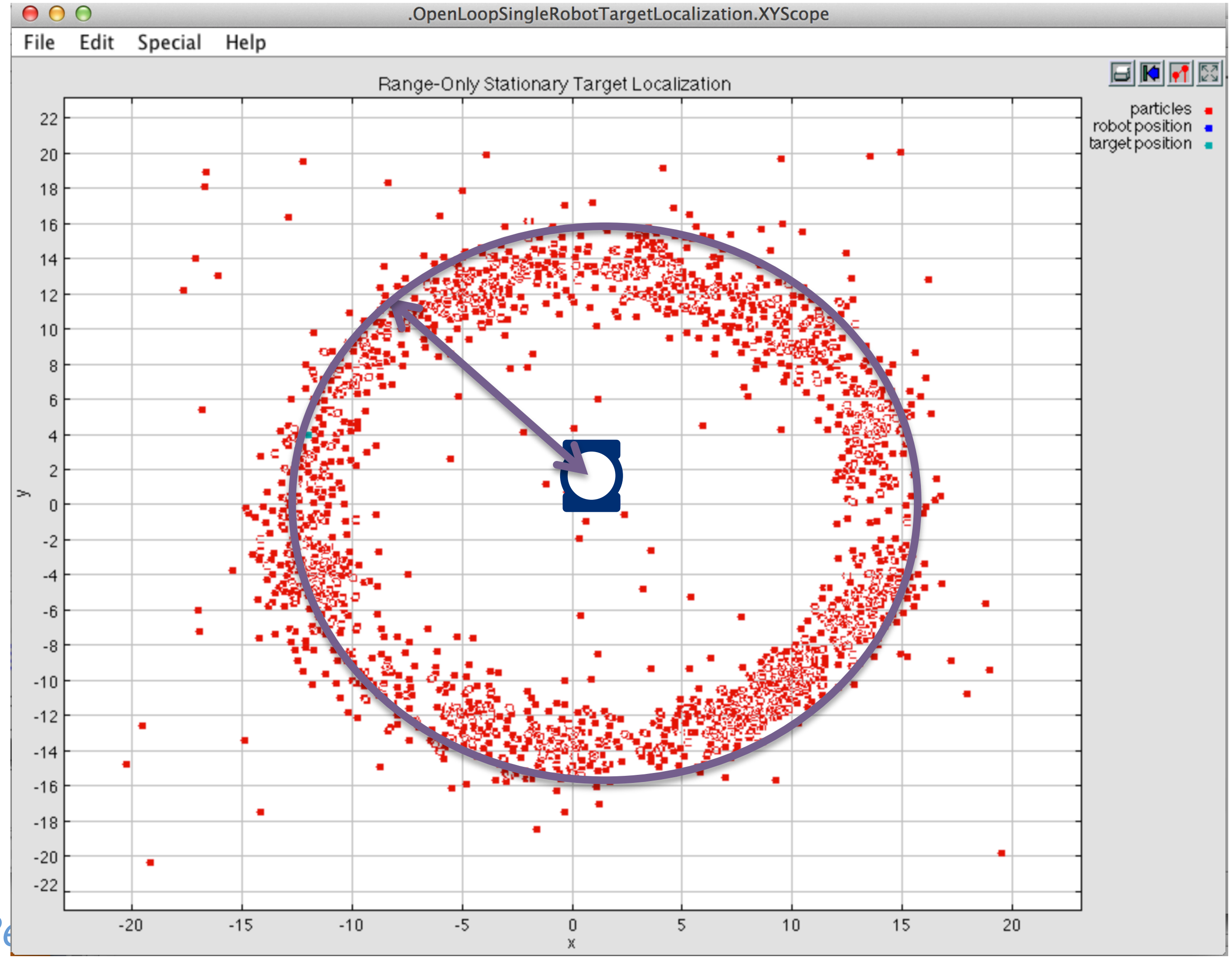
Particle Filter: Assigning Weights

- The particle weights (under Gaussian noise) would look like the following:



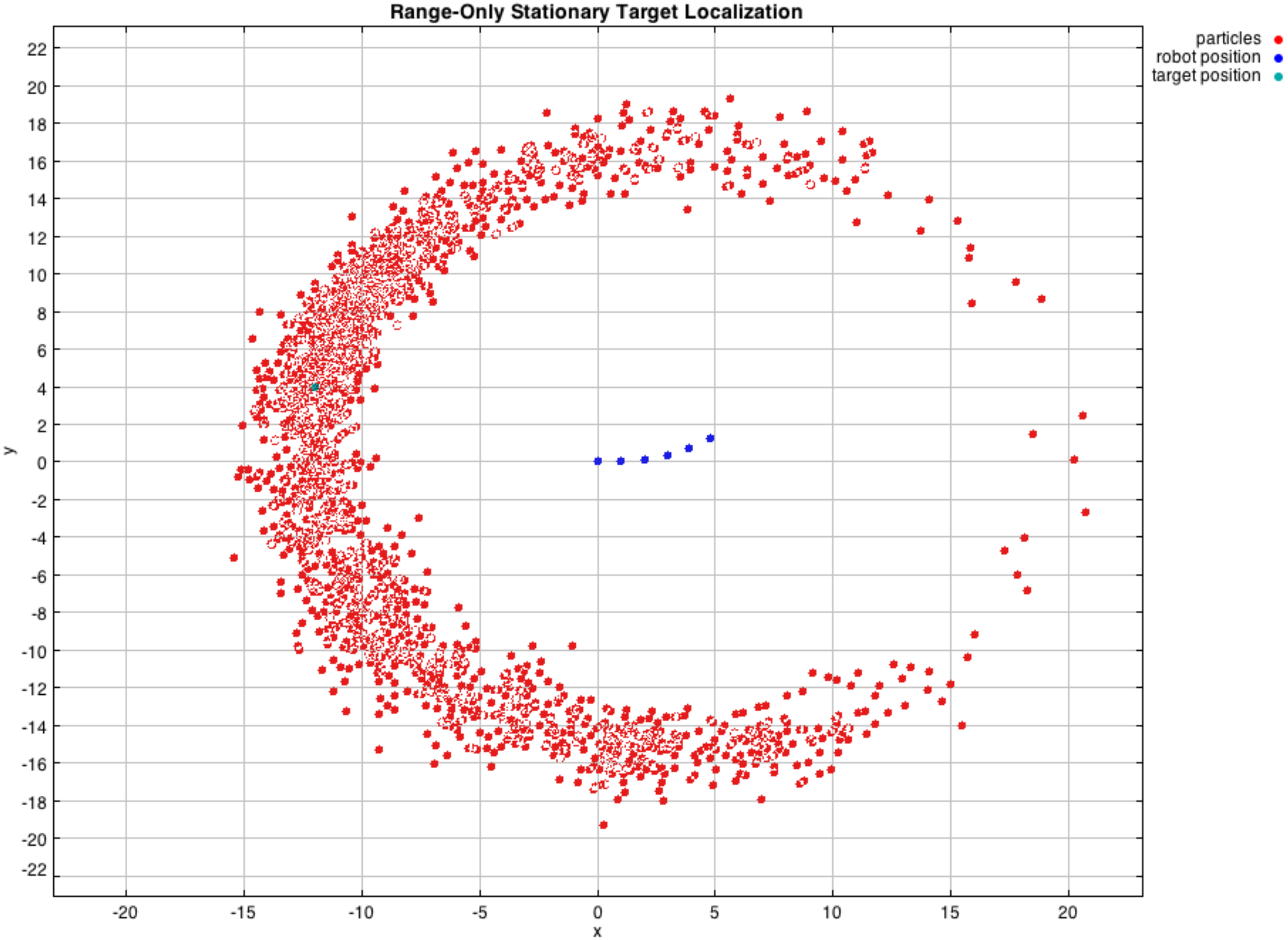
Particle Filter: Resampling

- The resulting set of particles would look like:

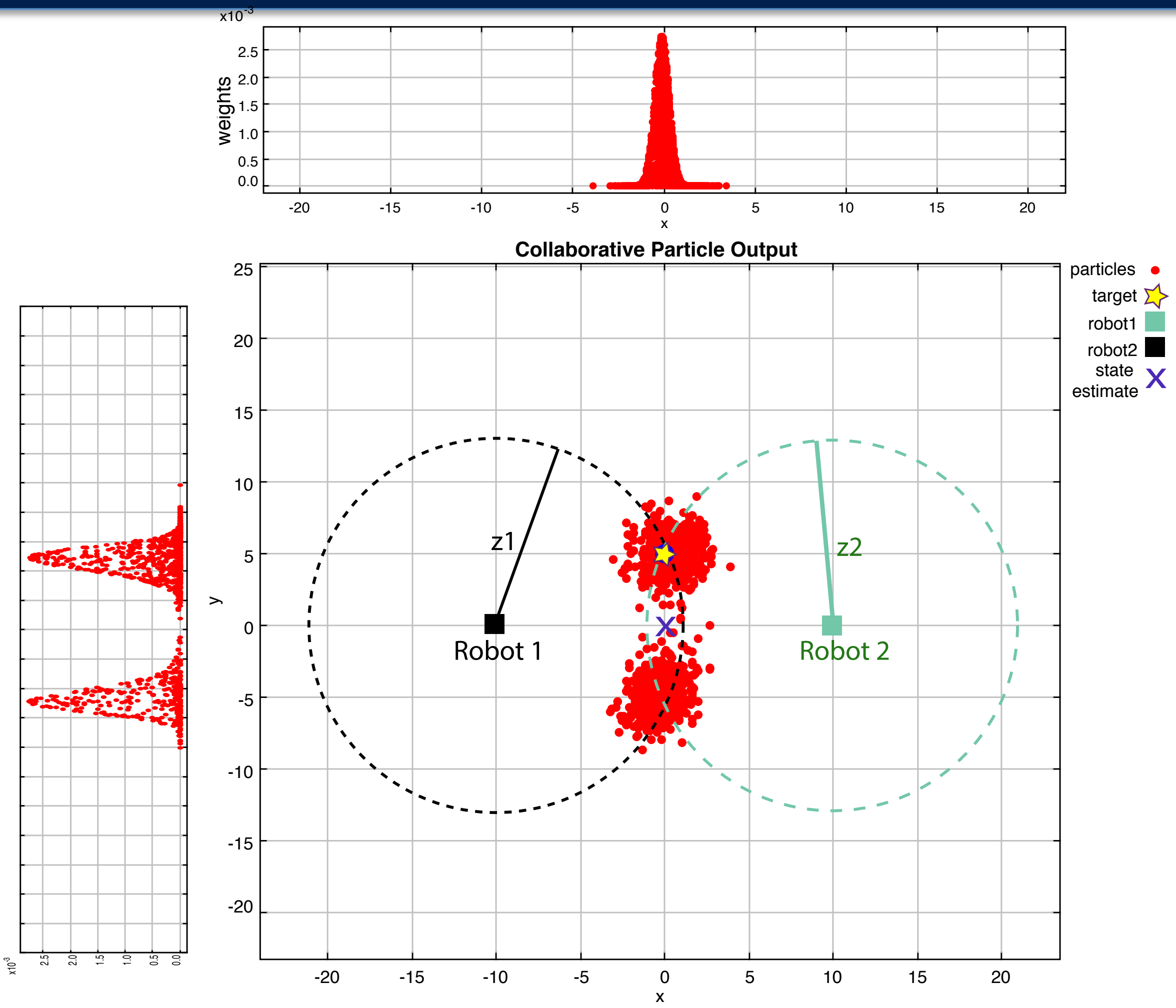


Particle Filter: Propagation

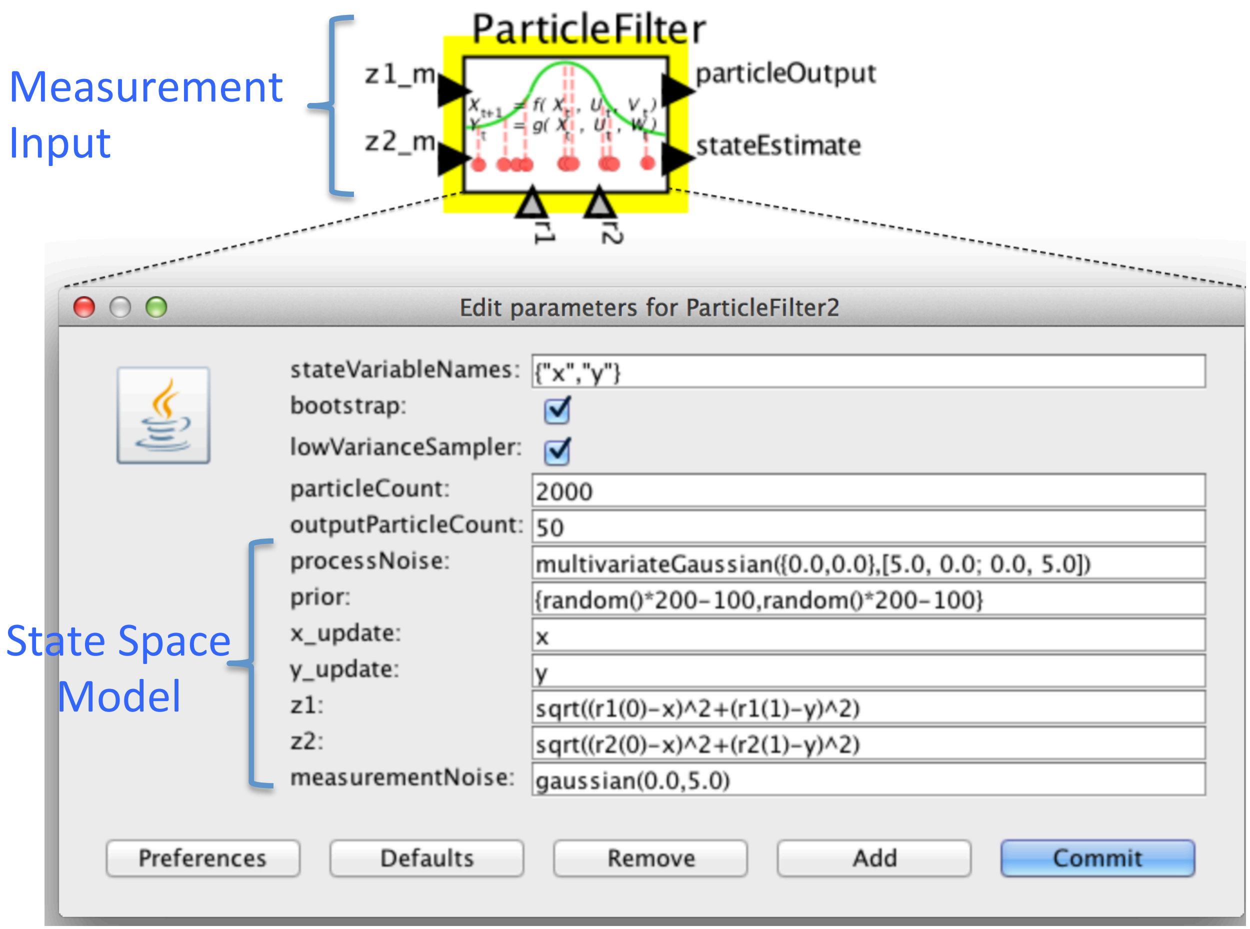
- Propagate resulting particles according to dynamics model



Particle Filtering with Range Sensors



Two-Observer Particle Filter



$$\theta_t = \begin{bmatrix} x_t \\ y_t \end{bmatrix}$$

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$$y_0 \sim \texttt{Uniform}([-100, 100])$$

$$\mathbf{z}_t = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

$$z_{it} = \|r_{it} - \theta_t\| + \omega_t, \; i = 1, 2$$

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Path Planning

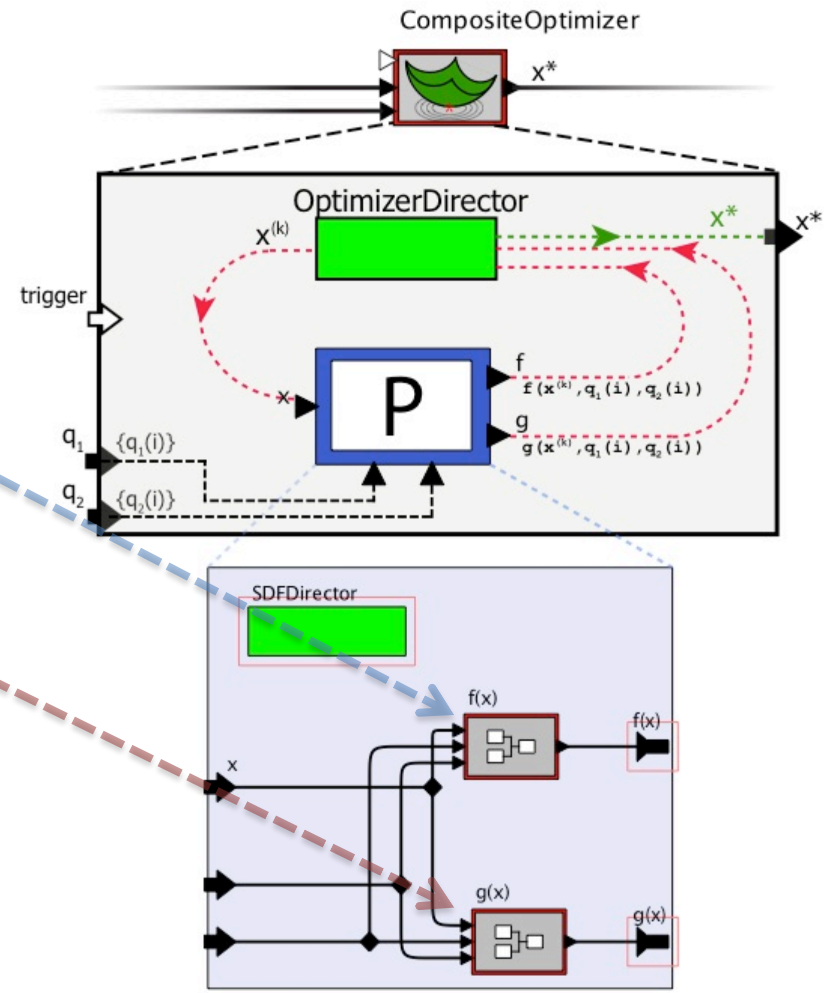
- One candidate metric to be used for online trajectory optimization: Information based methods: Mutual Information
  - A particle set is a good probabilistic measure of the *uncertainty* in a state variable
  - Size of particle set can be used to tune approximation bounds
- Optimization Goal: Maximize Mutual Information between measurements and particle set:
  - Locate intruder as precisely as possible, with fewest steps
- Can equivalently be formulated as: Minimize uncertainty in estimated intruder location

An Actor-oriented Optimizer

Consider the general constrained optimization problem of the form:

$$\underset{\mathbf{x}\in\mathbb{R}^n}{\text{minimize}} \;\; f(\mathbf{x}, \mathcal{Q})$$

$$\text{subject to} \;\; \mathbf{g}(\mathbf{x}, \mathcal{Q}) \geq 0$$



Currently supports: COBYLA, a gradient-descent constrained optimization solver

Cost Functions for Path Planning: Mutual Information

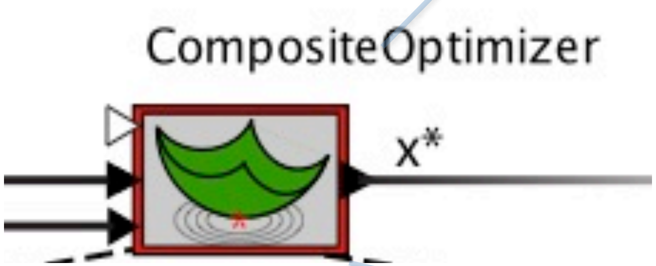
Optimization Goal: Maximize Mutual Information between future measurements and predicted particle set:

- Locate intruder as precisely as possible, with fewest steps

This can equivalently be formulated as: Minimizing the uncertainty in estimated intruder location. One-step optimal trajectories:

$$\mathbf{u_t}^* = \arg\max_{\mathbf{u_t}} \; I(z_{t+1}, x_{t+1})$$

$$\text{s.t } ||u_t^{(i)}|| \leq V_{max}, \;\; i = 1, 2, ..., M$$



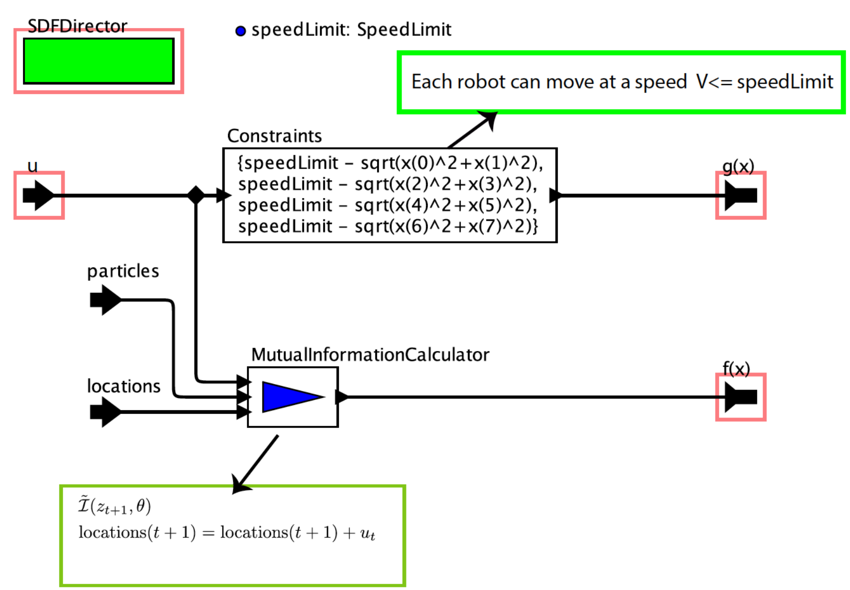
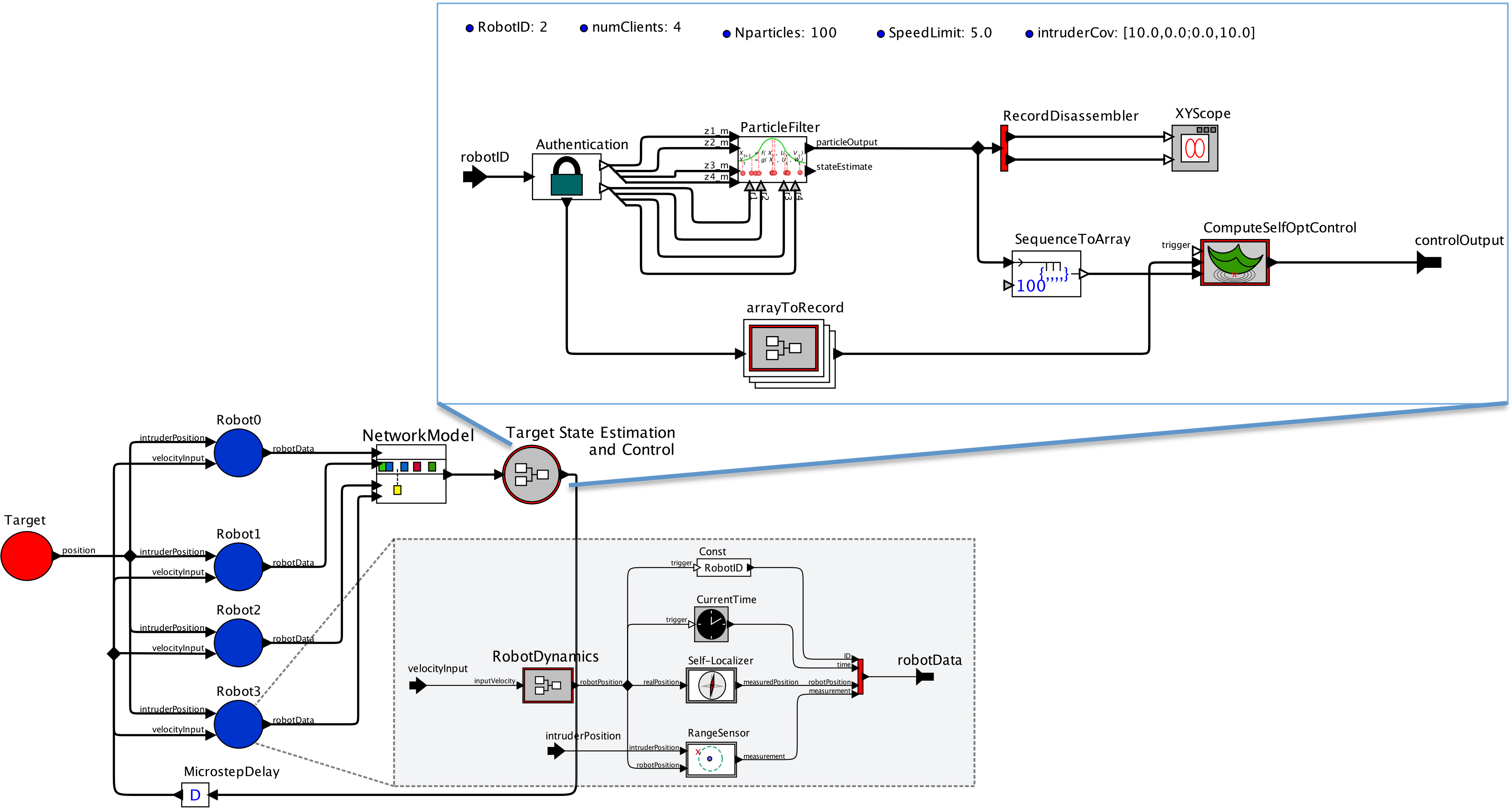
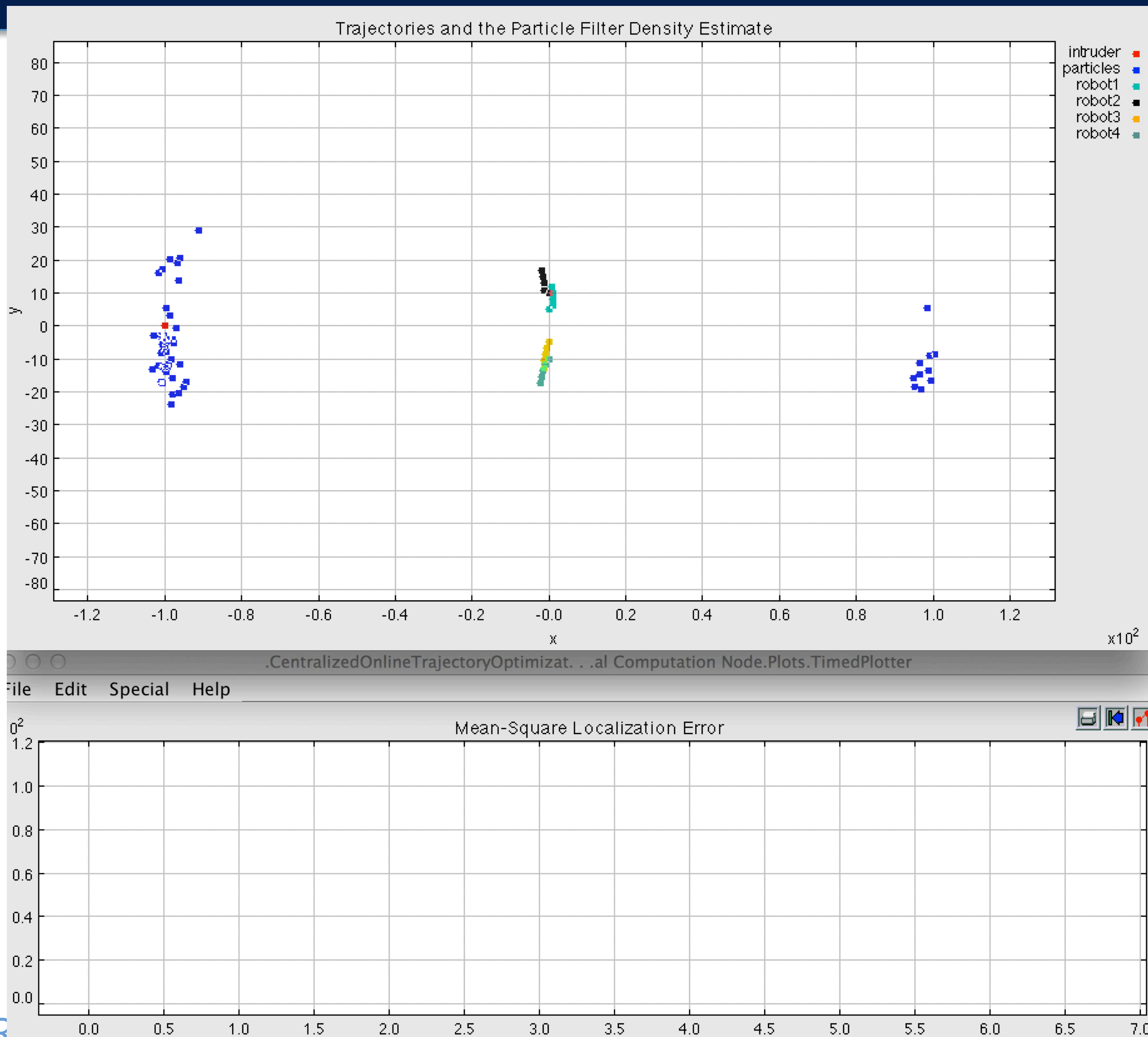


Figure : The system-level optimization problem for the WSN example

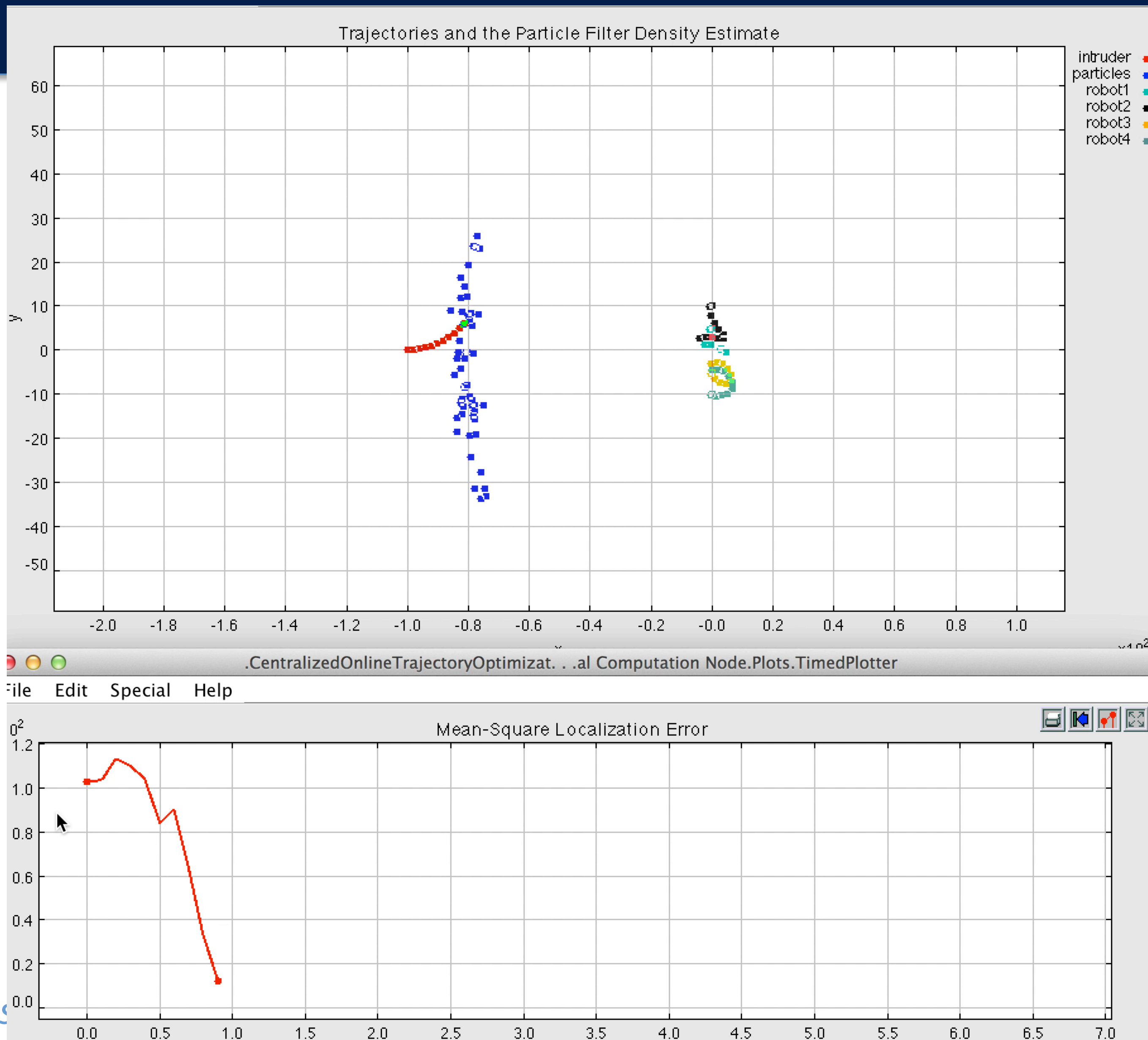
Cooperative Target Localization: Models



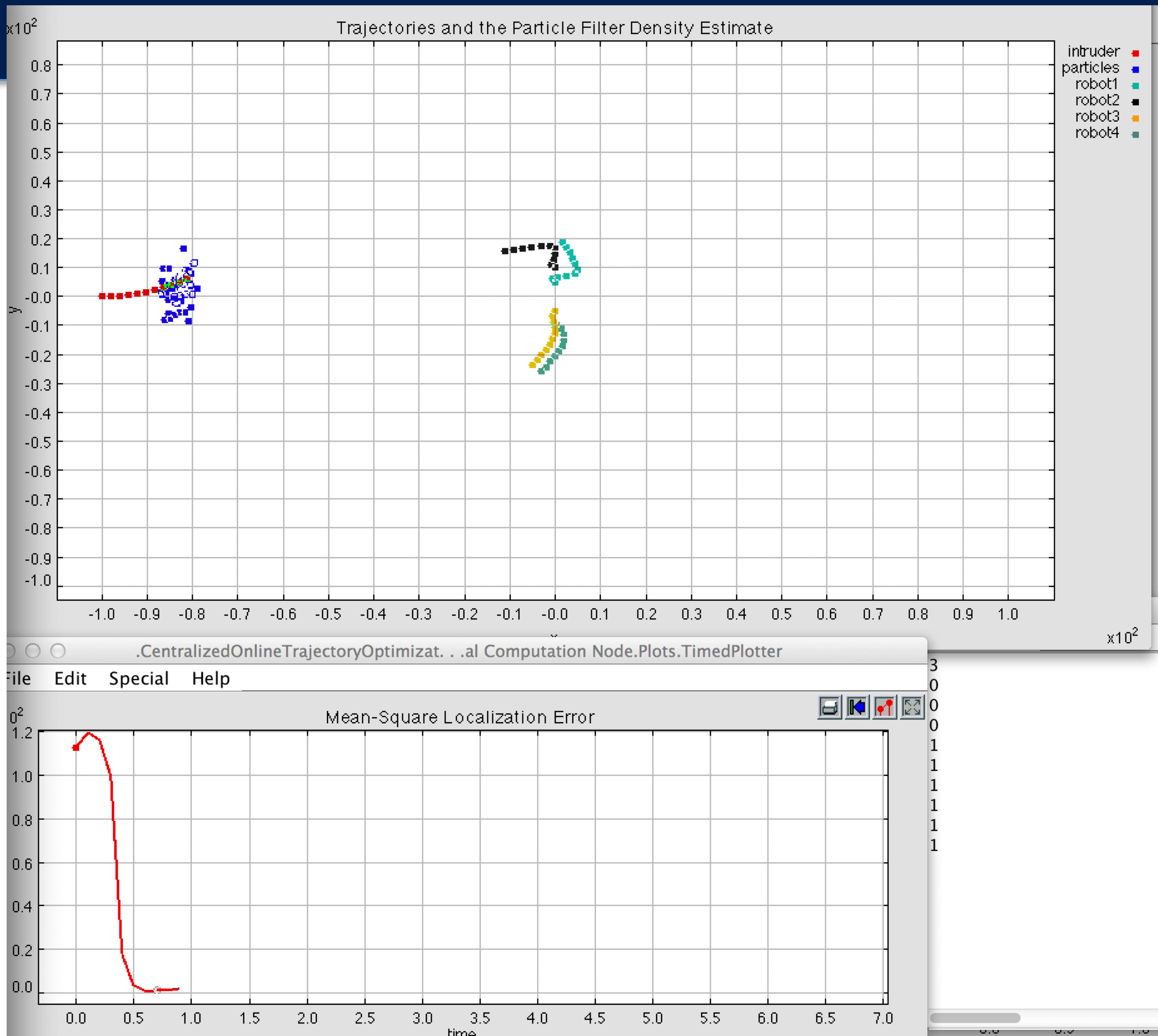
Demo: MI Maximization



Demo: Direct Pursuit



Demo: Hybrid Approach - 1 Follower

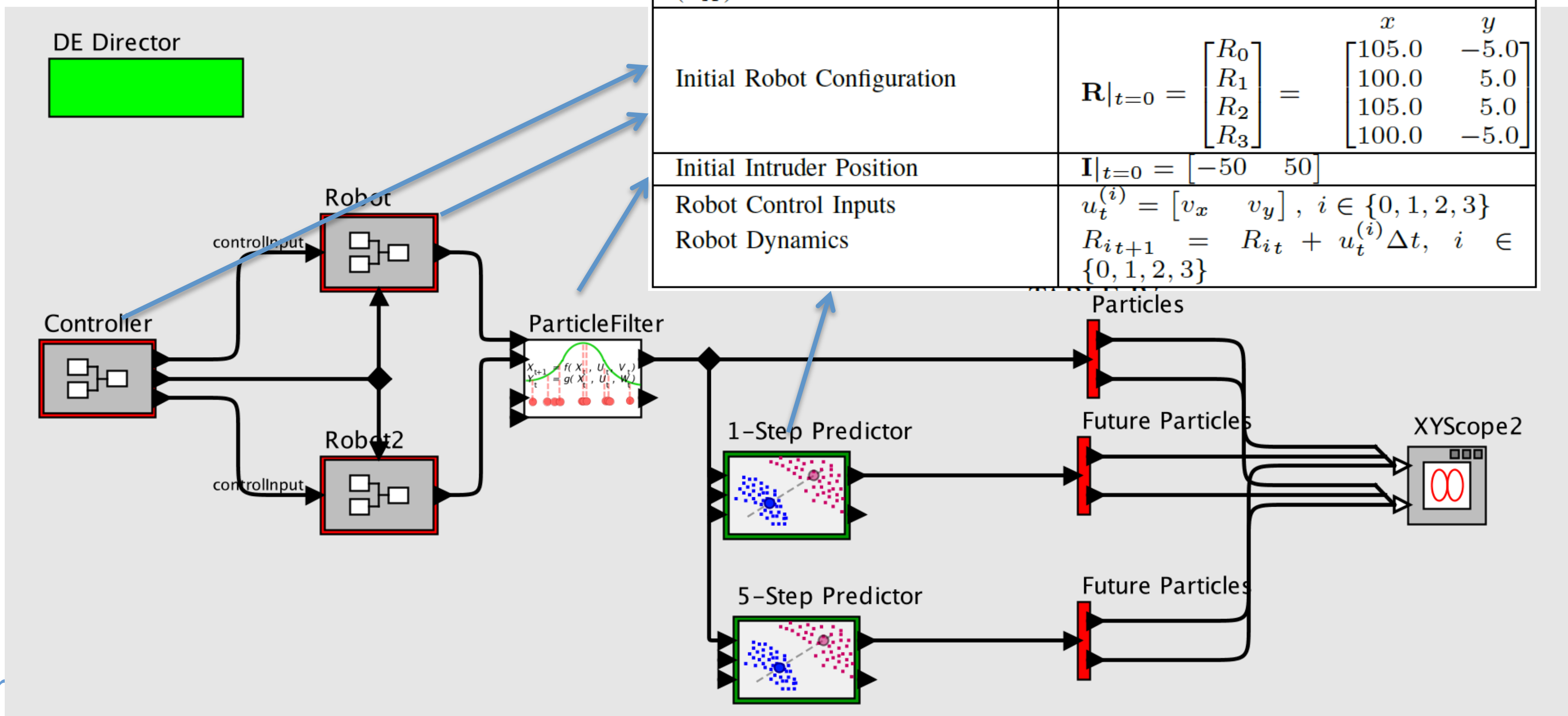


Bridging Actor-Oriented Modeling and ML Algorithms

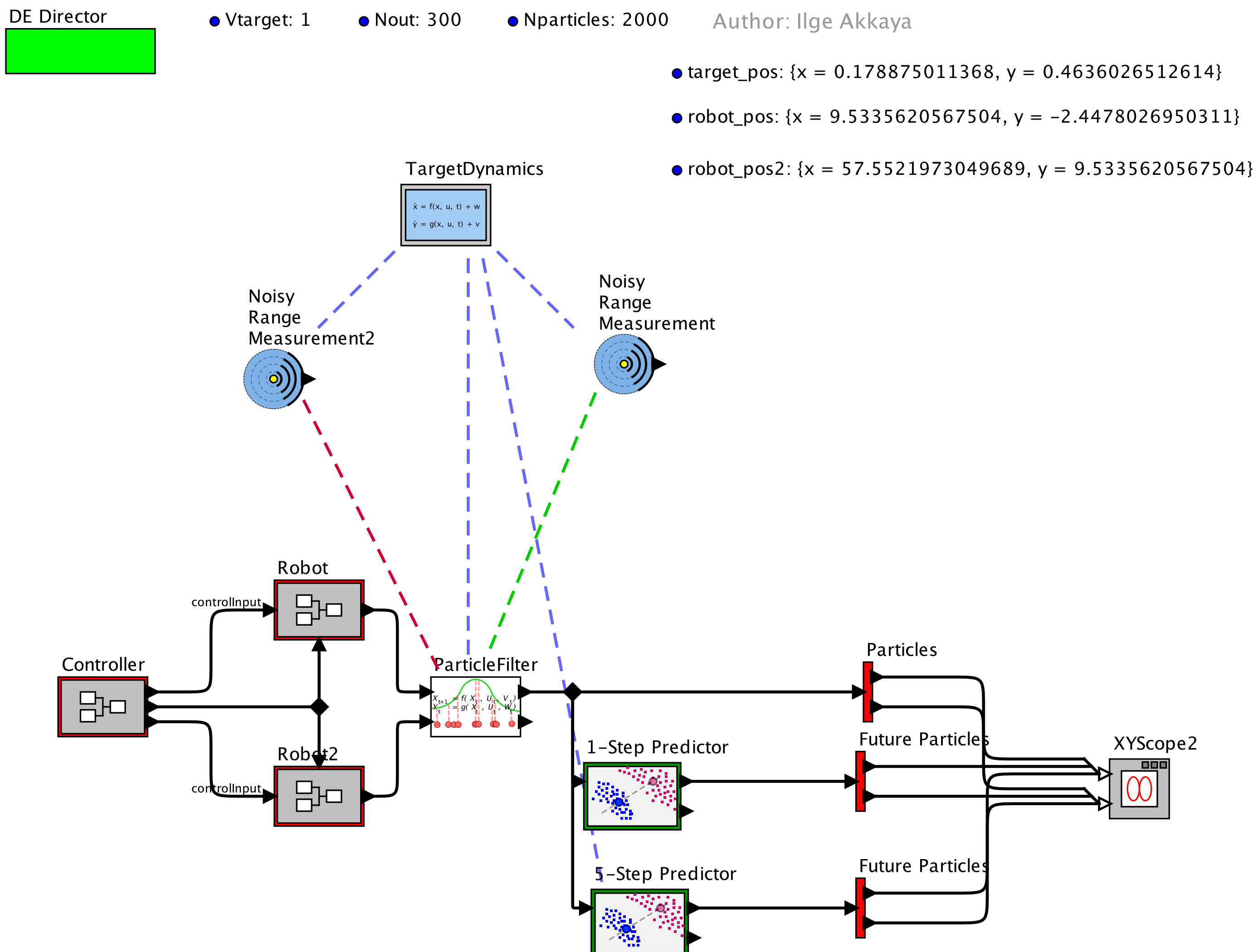
- Goal: ML Algorithms that are aware of the system models
- Methodology: Implement measurement models and system dynamics as decorator actors in the system model
  - Easy to share, consistent models of underlying system models
  - Scalable and unambiguous ML algorithm design for non-experts

Shared State Space Models for Model Predictive Control

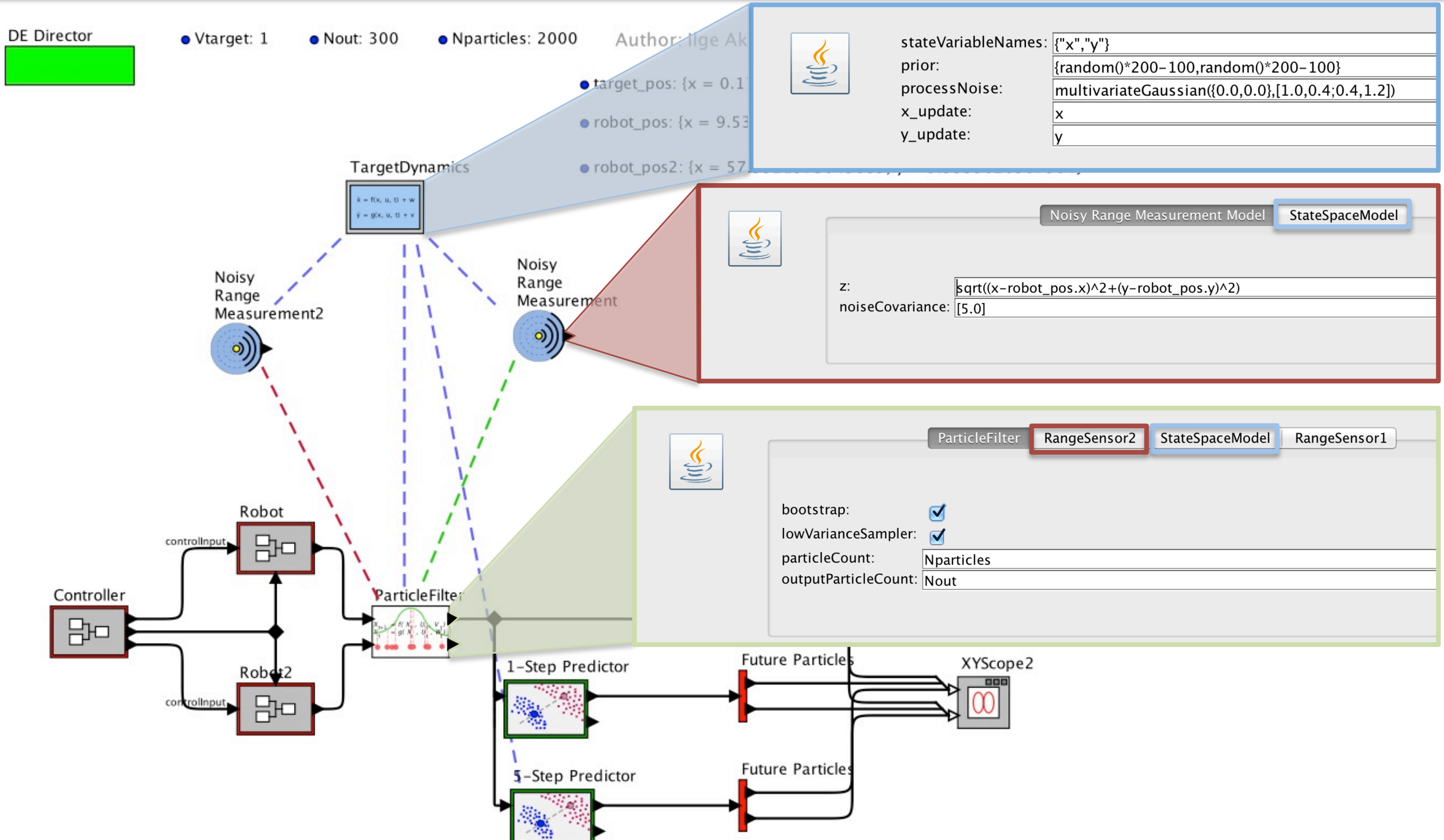
Simulation Parameter	Value
Size of Robot Team,M Search space Sensor measurement noise Maximum Robot Speed Iteration Frequency	4 200x200 units $\nu_t \sim \mathcal{N}(0, 5.0)$ 20 units/s 10 Hz
Target Dynamics Prior Belief on Target Position (π_X)	Circular Motion with $\omega = \pi/5$ Uniform over search space
Initial Robot Configuration	$\mathbf{R}\|_{t=0} = \begin{bmatrix} R_0 \\ R_1 \\ R_2 \\ R_3 \end{bmatrix} = \begin{array}{cc} x & y \\ \left[\begin{array}{cc} 105.0 & -5.0 \\ 100.0 & 5.0 \\ 105.0 & 5.0 \\ 100.0 & -5.0 \end{array}\right] \end{array}$
Initial Intruder Position	$\mathbf{I}\|_{t=0} = \begin{bmatrix} -50 & 50 \end{bmatrix}$
Robot Control Inputs Robot Dynamics	$u_t^{(i)} = \begin{bmatrix} v_x & v_y \end{bmatrix}, \; i \in \{0,1,2,3\}$ $R_{i\,t+1} = R_{i\,t} + u_t^{(i)} \Delta t, \; i \in \{0,1,2,3\}$



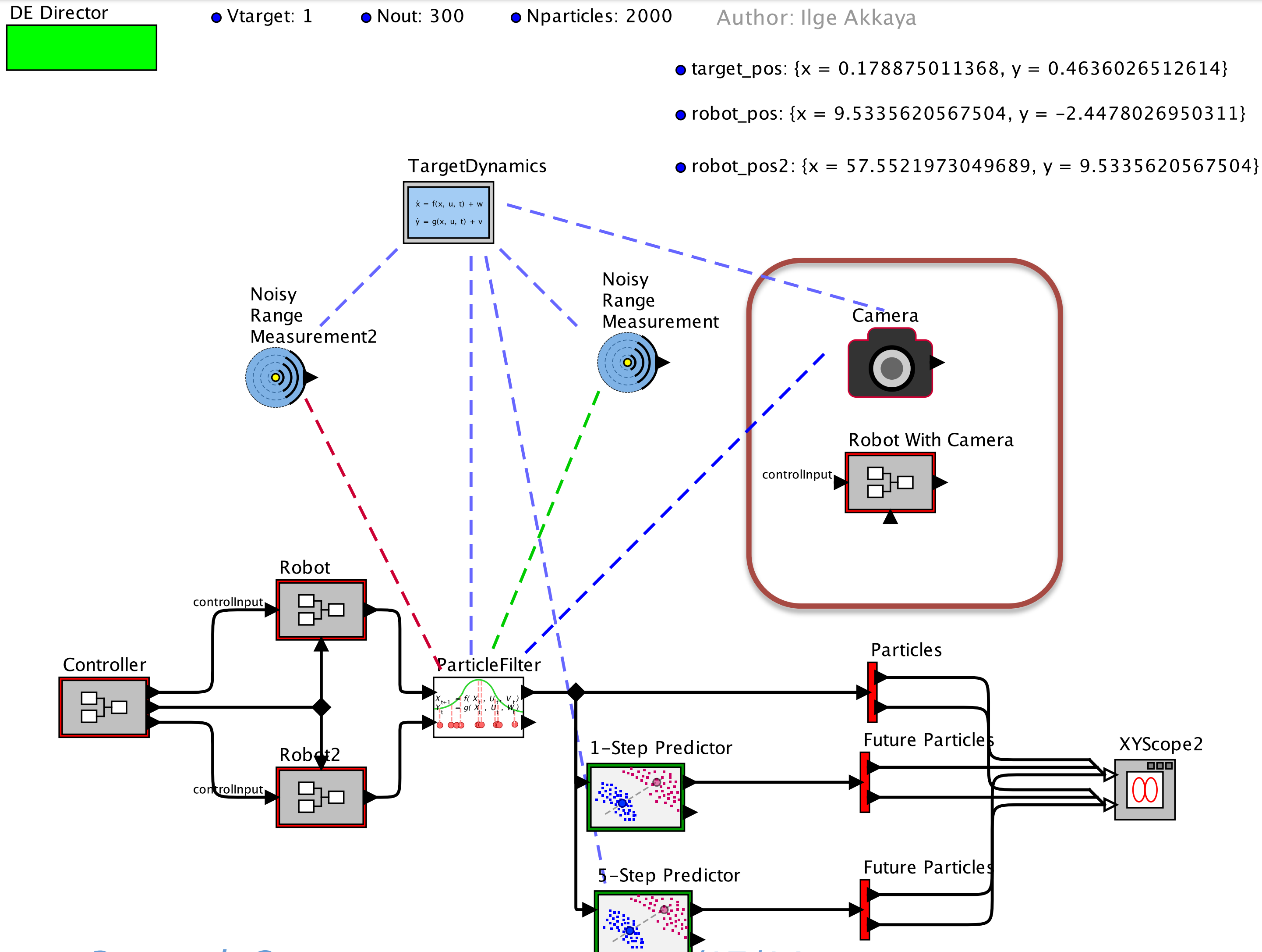
Measurement Models and Dynamics as Decorators



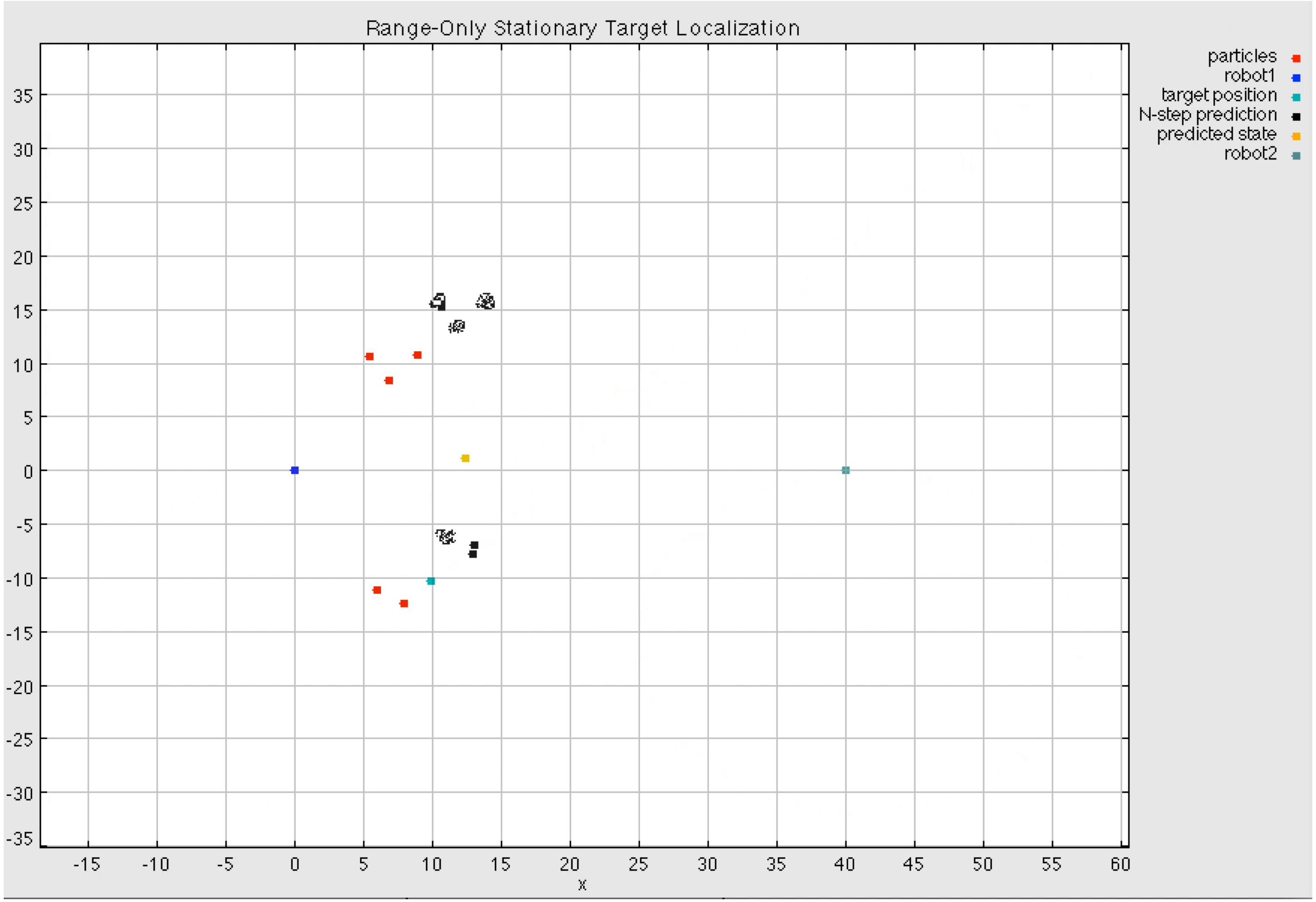
Measurement Models and Dynamics as Decorators



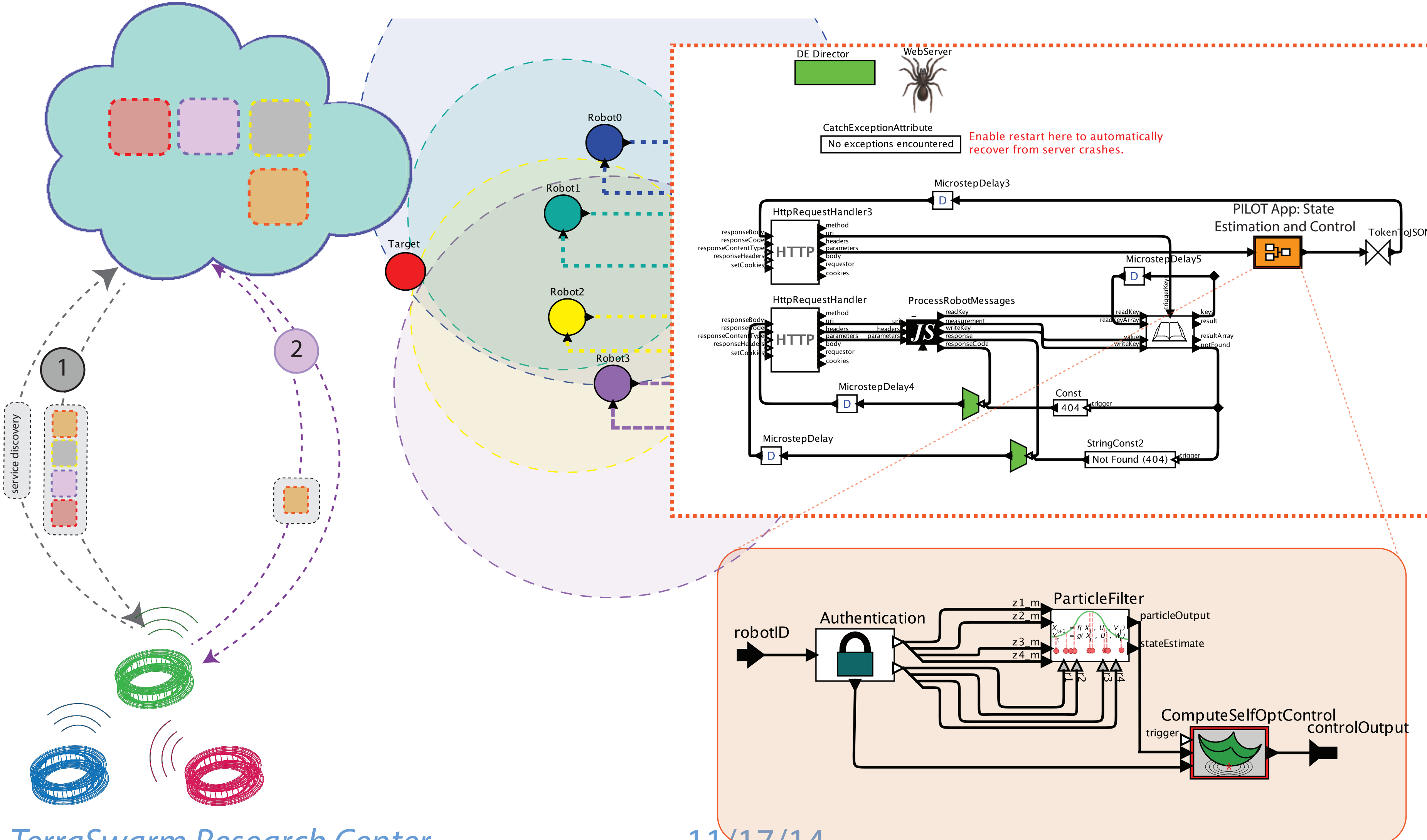
Target Localization: Adding a new Sensor



Demo: Prediction



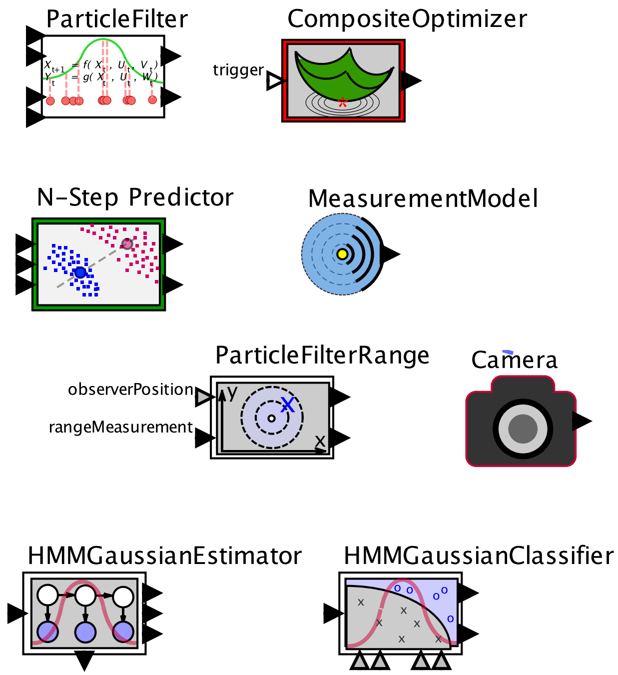
ML and Optimization: Swarmlets



Conclusions

Presented an actor-oriented machine learning toolkit that is designed for

- ML and Optimization applications on **streaming data**
- Enhancing **programmability** of *swarmlets*
- *Actor libraries for common state-space dynamics and sensor models*



Looking Ahead

- Enhancing ML capabilities:
  - *Discrete Optimization Solvers*
    - *(Mixed) Integer Programming*
  - *Tool Integration: e.g., GMTK*
- *Developing Swarmlets: Providing Services to TerraSwarm Application Developers*
  - *More case studies*
  - *Anomaly detection*
  - *Multi-sensor fusion*

Demos: Available in Ptolemy II

http://chess.eecs.berkeley.edu/ptexternal/

Optimization and Machine Learning

Control Improvisation

- Jazz Improvisation

Optimization

- Constrained Simple Linear Regression
- Simple Function Minimization

Particle Filter

- Multi Robot Intruder Tracking
- Online Robot Trajectory Optimization
- Online Robot Trajectory Optimization - Distributed Computation
- Open-Loop Target Localization - Single Robot
- Open-Loop Target Localization - Two Robots
- Multi-Observer Particle Filtering
- Particle Filter Range

Probabilistic Models

- Channel Fault Model
- Communication Anomaly Detection Using HMM Estimation
- Gaussian Mixture Model
- Gaussian Mixture Model Parameter Estimation
- Hidden Markov Model
- Hidden Markov Model Analysis
- Discrete-Time Markov Chain

Thank You !

Questions?
Comments?